Reliable Classification of High Explosive and Chemical/Biological Artillery Using Acoustic Sensors

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ABSTRACT

The Army is currently developing acoustic sensor systems that will provide extended range surveillance, detection, and identification for force protection and tactical security. A network of such sensors remotely deployed in conjunction with a central processing node (or gateway) will provide early warning and assessment of enemy threats, near real-time situational awareness to commanders, and may reduce potential hazards to the soldier. In contrast, the current detection of chemical/biological (CB) agents expelled into a battlefield environment is limited to the response of chemical sensors that must be located within close proximity to the CB agent. Since chemical sensors detect hazardous agents through contact, the sensor range to an airburst is the key-limiting factor in identifying a potential CB weapon attack. The associated sensor reporting latencies must be minimized to give sufficient preparation time to field commanders, who must assess if an attack is about to occur, has occurred, or if occurred, the type of agent that soldiers might be exposed to. The long-range propagation of acoustic blast waves from heavy artillery blasts, which are typical in a battlefield environment, introduces a feature for using acoustics and other sensor suite technologies for the early detection and identification of CB threats. Employing disparate sensor technologies implies that warning of a potential CB attack can be provided to the solider more rapidly and from a safer distance when compared to current conventional methods. Distinct characteristics arise within the different airburst signatures because High Explosive (HE) warheads emphasize concussive and shrapnel effects, while chemical/biological warheads are designed to disperse their contents over immense areas, therefore utilizing a slower burning, less intensive explosion to mix and distribute their contents. Highly reliable discrimination (100%) has been demonstrated at the Portable Area Warning Surveillance System (PAWSS) Limited Objective Experiment (LOE) conducted by Joint Project Manager for Nuclear Biological Contamination Avoidance (JPM NBC CA) and a matrixed team from Edgewood Chemical and Biological Center (ECBC) at ranges exceeding 3km. The details of the field-test experiment and real-time implementation/integration of the standalone acoustic sensor system are discussed herein.

1. INTRODUCTION

The Army is currently developing acoustic sensor systems that will provide extended range surveillance, detection, and identification for force protection and tactical security. A network of such sensors remotely deployed in conjunction with a central processing node (or gateway) will provide early warning and assessment of enemy threats, near real-time situational awareness to commanders, and may reduce potential hazards to the soldier. In contrast, the current detection of CB agents expelled into a battlefield environment is limited to the response of chemical sensors that must be located within close proximity to the CB agent. Since chemical sensors detect hazardous agents through contact, the sensor range to an airburst is the key-limiting factor in identifying a potential CB weapon attack. The associated sensor

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reporting latencies must be minimized to give sufficient preparation time to field commanders, who must assess several situations of the enemies' strategy, as well as factoring the exposure time and types of agents the soldiers could encounter on the battlefield. The long-range propagation of acoustic blast waves from heavy artillery blasts, which are typical in a battlefield environment, introduces a feature for using acoustics and other disparate sensor technologies for the early detection and identification of CB threats. Employing disparate sensor technologies implies that warning of a potential CB attack can be provided to the solider more rapidly and from a safer distance in comparison to conventional methods lessening exposure time for the soldiers. This capability facilitates the need for classifying the types of rounds that have burst in a specified region in order to give both warning and provide identification of CB agents found in the area. The additional information incorporated into the common operating picture will help field commanders (more) accurately plan and execute measures that must be taken in order to ensure the proper precautions to a mission [7]. Such a warning system would also help reduce the time-consuming, manpower intensive and dangerous tasks associated with identifying the airburst, allowing a field commander to make rapid and accurate judgments that insure greater safety and lessen exposure for the soldiers.

This paper supports acoustic sensor technologies to differentiate among conventional, i.e. HE, and CB artillery blasts using robust characteristics that remain unchanged with long-range wave propagation and degradation, firing time and detonation (either air or ground). The outcome illustrated herein is based on an analysis conducted using acoustic signature data collected during two independent data collection exercises and a third exercise that was conducted to demonstrate the algorithms in a real-time environment. The principal set of artillery blast data was collected at YUMA Proving Ground on 11-12 August 1995 in a field test experiment conducted by the National Center of Physical Acoustics (NCPA) at the University of Mississippi in collaboration with Acoustic Center of Excellence (ACOE) at Picatinny Arsenal. The reason for the experiment was to study if CB artillery blasts could be distinguished from HE blasts via acoustic and seismic sensor technologies. The field test consisted of point detonation and/or airburst of three categories of explosive rounds; two categories of artillery rounds considered analogous to chemical and biological warheads, and generic HE rounds most commonly used in the battlefield. The data set comprised of 8 ground impacts from HE rounds, 23 ground impacts from a Type A CB round and 8 air-bursts from a Type B CB round. The data was collected at seven sensors sites as shown in Figure 1. The rounds were fired from a self-propelled howitzer situated several kilometers to the west of a linear array of 5 sensor locations designated along an axis offset from the firing radial by 700m (cf. Figure 1). Sensor site S3 coincides with the ordinate axis of the estimated projectile impact point at 5km from the firing position. Microphones were emplaced at sensor sites S2, S4, S1 and S5 at a distance of 500m, 600m, 1000m and 1200m from S3, respectively. Geophones accompanied the microphones at positions S3 and S5, and a flash detector was emplaced at position S6, 2000 meters from S3. An acoustic transducer was positioned at site S7, 400m from S3 and in line with the estimated projectile impact point.
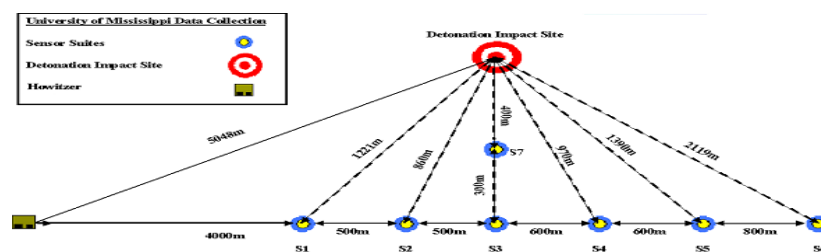

Figure 1 – Sensor Deployment at Yuma Proving Grounds

A preliminary investigation conducted by researchers at the National Center for Physical Acoustics has shown distinctive differences between airburst signatures from the three types of rounds, and a subsequent

study identifies potential features within the blast waves that could be used to discriminate between HE and CB blasts acoustically [1]. In this study, the rapid ignition of the HE rounds was found to generate larger amplitude, shorter duration signatures in contrast to the longer duration signals representative of the slower burning phosphorus, ignited in the Type A shell upon ground impact. It was determined that accurate range information from the multiple sensor positions to the blast event location would permit the use of amplitude alone to identify a CB round from its conventional HE counterpart. Discriminating attributes such as high frequency precursor signals produced by the passing of supersonic shrapnel elements from the exterior of HE rounds were identified prior to the main blast wave and noticeable at ranges up to 1 km, absent from CB rounds.

A second set of experimental data was collected at Dugway Proving Ground (DPG) to examine if acoustic, seismic, and imagery sensors could be exploited in order to distinguish conventional HE projectiles from those filled with either chemical and/or biological agents [2]. During this test exercise, two hundred and sixty rounds were fired, approximately half of which were fused to detonate on impact, while the other half were fused to detonate in the air. The HE rounds contained a larger amount of explosives when compared to the simulated chemical rounds specifically developed to detonate and release a fill consisting of polyethylene glycol and water. The data examined in this paper was collected from three sensor sites arranged in a triangle and numbered according to range from the detonation zone. Site 1 and site 3 were situated on the same radial line from the expected detonation area at ranges of 540m and 1665m respectively. Site 2 was positioned 1026m radially outward and 514m to the left of said location.

Numerous studies have been conducted that have created a wealth of research concerning the discrimination of HE and CB rounds using disparate sensor technologies [2]. Both time and frequency domain approaches were isolated to obtain features useful in the discrimination between HE and CB rounds. Time domain discriminating features were identified within the blast envelope, including the shrapnel noise reported in [1], and frequency domain features such as the instantaneous and maximum bandwidth.

A third field exercise/data collection was conducted to test and benchmark the real-time performance of the CBRN discrimination algorithm developed by ARDEC. The JPM NBC CA office provided ARDEC the opportunity to use the PAWSS system as a test platform for the algorithm described herein developed by the ACOE [6]. The PAWSS platform contained MET sensors, Mid Range Radar, Stand-OFF CB sensor, Long Range Radar, Point CB sensors, Battlefield Warning software and Surveillance Systems providing a one stop CBRN detection solution. The artillery airburst portion of the experiment was held between 20-22 June 2005 as part of the PAWSS LOE conducted by JPM NBC CA and their team matrixed from ECBC.

The most distinctive characteristics of each blast type are easily identified in Figure 2; the high frequency precursors from the HE blast prior to the main blasts as shown in Figure 2a, the comparatively slow burn and weak under pressure associated with the Type A CB blast in Figure 2b, and a short duration pulse that precedes the slow burn of agents within the Type B Base ejection rounds shown in Figure 2c. We show that range invariant features found within the multiresolution decomposition of the corresponding signatures in an attempt to further promote disparate sensor technology for CB/HE discrimination. The subsequent growth of a feature space representation for classification is based upon data acquired during separate data collection exercises, that when combined, introduce variations within the intraclass and interclass attributes for the HE and Type A CB artillery blasts. This is principally due to the different types of payloads used to simulate CB rounds, differences in the local environment and data acquisition hardware used, and variations in range and aspect angle of the blasts with respect to sensor emplacement positions. We show that information extracted via different levels of decomposition produce repeatable properties that can be combined to ensure reliable discrimination between HE and CB blasts.
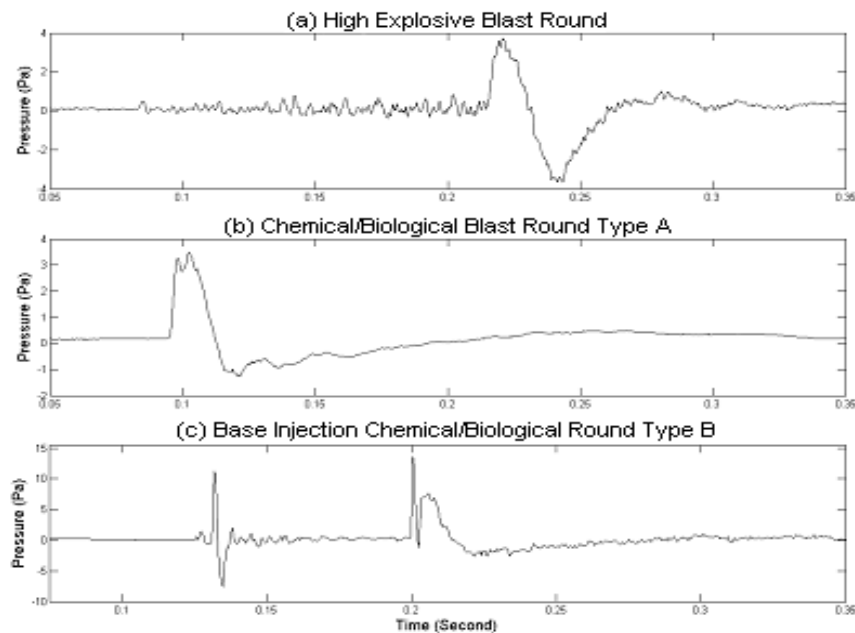
**Figure 2 – Acoustic Signatures from (a) HE blast recorded at DPG, (b) Type A Simulated CB
Round burst recorded at DPG and (c) Air burst for the Type B White
Phosphorus Base Injection round recorded at YPG**

2.   WAVELET FEATURE EXTRACTION FOR CLASSIFICATION

Wavelet analysis is used to identify distinct feature sets that remain consistent for a given class of artillery round, and do not degrade significantly with long-range propagation. Figure 2 shows the complex, non-stationary response of the signatures to be evaluated, which are categorically poor candidates for feature extraction and segmentation via Fourier analysis or the short-time Fourier Transform. On the other hand, the non-stationary, transient and often oscillatory nature of these signals is readily characterized with wavelet bases that effectively capture the time-frequency distribution of such signal components. Wavelets are better suited for analyzing transient signals, as they are well localized in time and in frequency, and are able to take into account the scale of multiple signal components [3]. To this end, the wavelet transform can provide a scalable time-frequency representation of artillery blast signatures and provides details that are not readily found using conventional signal processing techniques. Noise components that are introduced into the blasts waves prior to being received at the sensor are also a serious impediment to isolating features that can be used to efficiently characterize the signal. Multiresolution analysis will also isolate this noise and remove it from the baseband signal of interest; a process referred to as wavelet denoising. Wavelet denoising is optimal in that noise components are removed from signal components regardless of the frequency content of the signal, which is by far more effective than conventional filtering methods.

2.1 Discrete Wavelet Transform and Multiresolution Analysis

The discrete wavelet transform (DWT) is derived from subband filters and based on a multiresolution decomposition of a signal to give a coarser and coarser approximation to the original signal by removing high frequency detail at each level of decomposition [4]. In other words, the wavelet transform is a multiresolution transform that maps low frequency information of signals into a coarsely sampled subspace and maps high frequency information into more finely sampled subspaces. The DWT is defined by the scaling function

$$\phi(x) = 2^{1/2} \sum_{k=0}^{L-1} h_{k+1} \phi(2x - k) \qquad (1)$$

and a wavelet function:

$$\psi(x) = 2^{1/2} \sum_{k=0}^{L-1} g_{k+1} \phi(2x - k) \qquad (2)$$

where h_k and g_k are analysis filters. It is important to choose the appropriate filter, in order to retain the characteristics of the transient signals. . The choice of the wavelet scaling function should have properties similar to the original signal because the quality of wavelet decomposition depends significantly on the ability to approximate the signal with wavelets [3]. The output of the wavelet transform shows the correlation between the signal and wavelet as a function of time. The easiest method for selecting a wavelet is to copy a signal's time-frequency behavior, however, most transient signals cannot be used as wavelet basis functions since they resemble exponentially damped sinusoids and do not possess a zero mean. The wavelet basis used in this paper is the db5 wavelet defined by Daubechies [3] that has the scaling function and translation function shown in Figure 3(a), and 3(b) respectively.
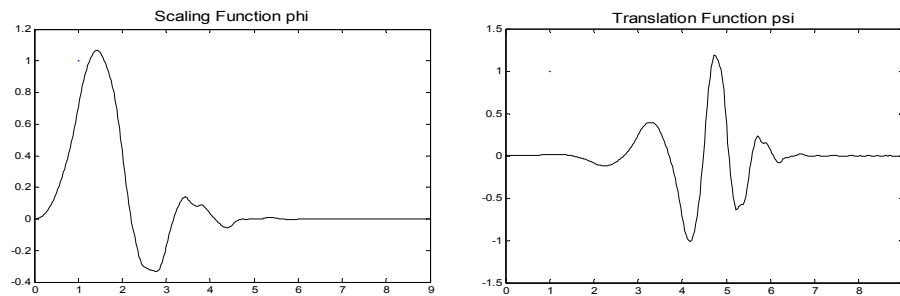

Figure 3 – Daubechies wavelet n =5 (a) Scaling Function (b) Translation Function

Note that scaling function strongly resembles the blast signature for the HE and "Type A CB signals" shown in Figure 3a and 3b, as well as the short pulse preceding the main blast in Figure 2c. A multiresolution filter bank using low pass and high pass wavelet filters as shown in figure 4 is used to implement the DWT and to decompose an input signal into different frequency bands is used to implement the DWT. At each level of decomposition, the high pass filter defined in (2) produces the detail information, D_n, while the low pass filter associated with the scaling function in (1) produces the coarse approximations A_n. Often referred to as the Mallat algorithm a process of successive lowpass and high pass filtering of the input signal is used to implement the DWT [5]. The resulting banks of dyadic multirate filters split the input signal into subbands at each level of decomposition produces a signals with a subset of frequencies spanning half of the original frequency band. If the original signal is sampled at a frequency of fs Hz, then the output of the first high pass filter which is the first detail coefficient D_1, captures the band of frequencies between fs/2 and fs/4. In the same manner, the highpass filter in the second stage captures signal components with a bandwidth between fs/4 and fs/8, and so on. In this way, arbitrary resolution in frequency can be obtained. Since the input signal at each stage of decomposition contains the highest frequency equivalent to twice that of the output stages, it can be sampled at half the original sampling frequency, thus discarding half the samples with no loss of information. This decimation by a factor of 2, reduces the time resolution of the entire signal as the input signal is represented by half of the total number of samples and effectively doubles the scale.
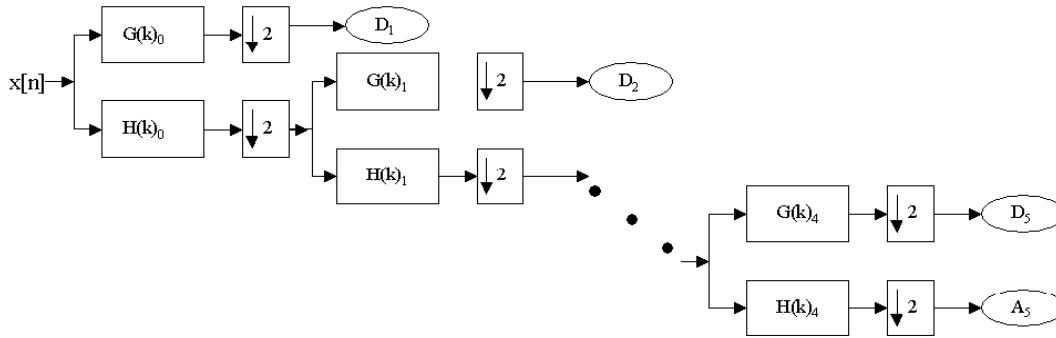
Figure 4 – A Multirate Filter Bank used as a Five Level Wavelet Decomposition Tree

2.2 Wavelet Features for Classification

Figures 5 (a-c) show blast waves from the three unique artillery rounds of interest, followed by four signals derived from the multiresolution decomposition with the coefficients at level 5 and detail signals at level 5, 4, and 3 respectively. The proposed feature space is comprised of primitives derived from the normalized energy distributions within the details at level 5, 4, and 3, centered about the maximum value of the blast wave. A fourth feature is obtained from the coefficients at level 5. Features such as the rise time for the blast wave and the low frequency content found within the acoustic signals is least attenuated over long propagation distances when compared to some of the predominant features initially identified for discrimination. From the plots in Figure 5, it can be seen that at varying levels of decomposition beyond level 2, the energy distribution within the details differ dramatically prior to the max peak pressure of each blast with respect to energy distributions after the main blast has occurred. Furthermore, this energy is not amplitude dependant as the baseband signal is filtered by the scaling function and only the high-frequency noise components are captured within the details after decomposition.

Let t_P denote the sample time where the maximum peak over pressure of a blast wave occurs. Let $t_0 = \alpha * f_s$ designate an integration start time, and $t_F = \beta * f_s$ denote integration stop time. We restrict the values α, β such that $0 < \alpha, \beta \leq 1$ for $t_P > t_0$ and $t_F > t_0$ such that $t_P, t_0, t_F \in I$. Define the energy distribution within the details just prior to the max peak pressure as

$$D_k^- = \frac{1}{N} \sum_{n=t_0}^{t_P} |D_k(n)| \qquad (3)$$

where $N = t_P - t_0$. Define the energy distribution at the point immediately after the max pressure occurs as

$$D_k^+ = \frac{1}{M} \sum_{m=t_P}^{t_F} |D_k(m)| \qquad (4)$$

where $M = t_F - t_P$. Since $D_k^-, D_k^+ > 0$ we are able to define analytic features $x_{Dk} \in \Re^k$ using the ratio of the normalized energy distributions within the details.

$$x_{Dk} = \log_{10}\left(\frac{D_k^-}{D_k^+}\right) \qquad (5)$$

The first 3-tuple of the features space consists of x_{D5}, x_{D4}, x_{D3} which we propose are useful to characterize the artillery blasts of interest. A fourth feature is derived from the wavelet coefficient obtained at level 5. We integrate the magnitude of the area for the coefficients between the start and stop times defined for the details

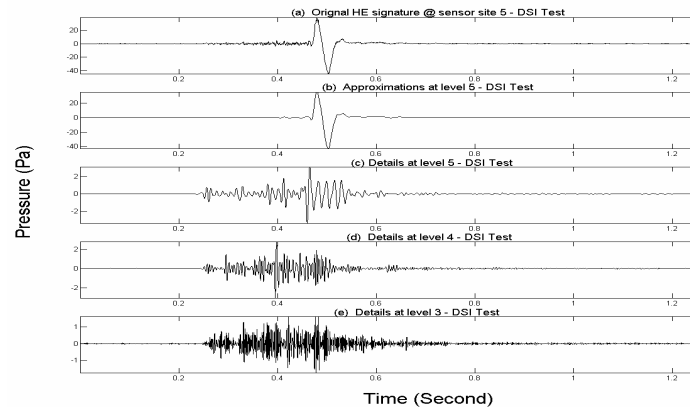$$A_{5AREA} = \log_{10}\left(\frac{1}{K}\sum_{k=t_0}^{t_F}|A_5(k)|\right) \qquad (6).$$

Figure 5a – HE Signal and Wavelet Decomposition to Level 5
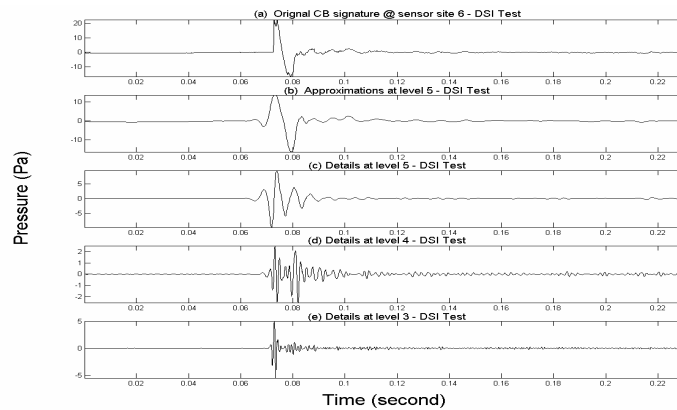

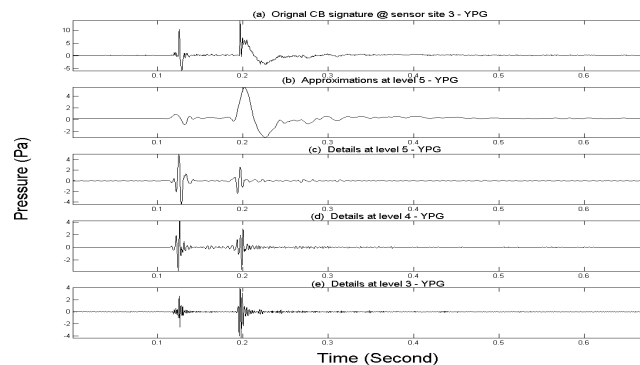**Figure 5b – Type A CB: Original Signal and Wavelet Decomposition to Level 5**

Figure 5c – Type B CB: Original Signal and Wavelet Decomposition to Level 5

Figure 6 (a-f) shows all permutations of 2-D subspaces for the entire set of data collected at Dugway Proving Ground that was used to train and initially benchmark the performance of a neural network classifier. An 'x' is used to indicate features derived from the CB blasts while the corresponding HE feature points are depicted with a '.' Note that the resulting subspaces reveal a high degree of separability, notwithstanding the 540 – 1660m variability in range at which the data was acquired.
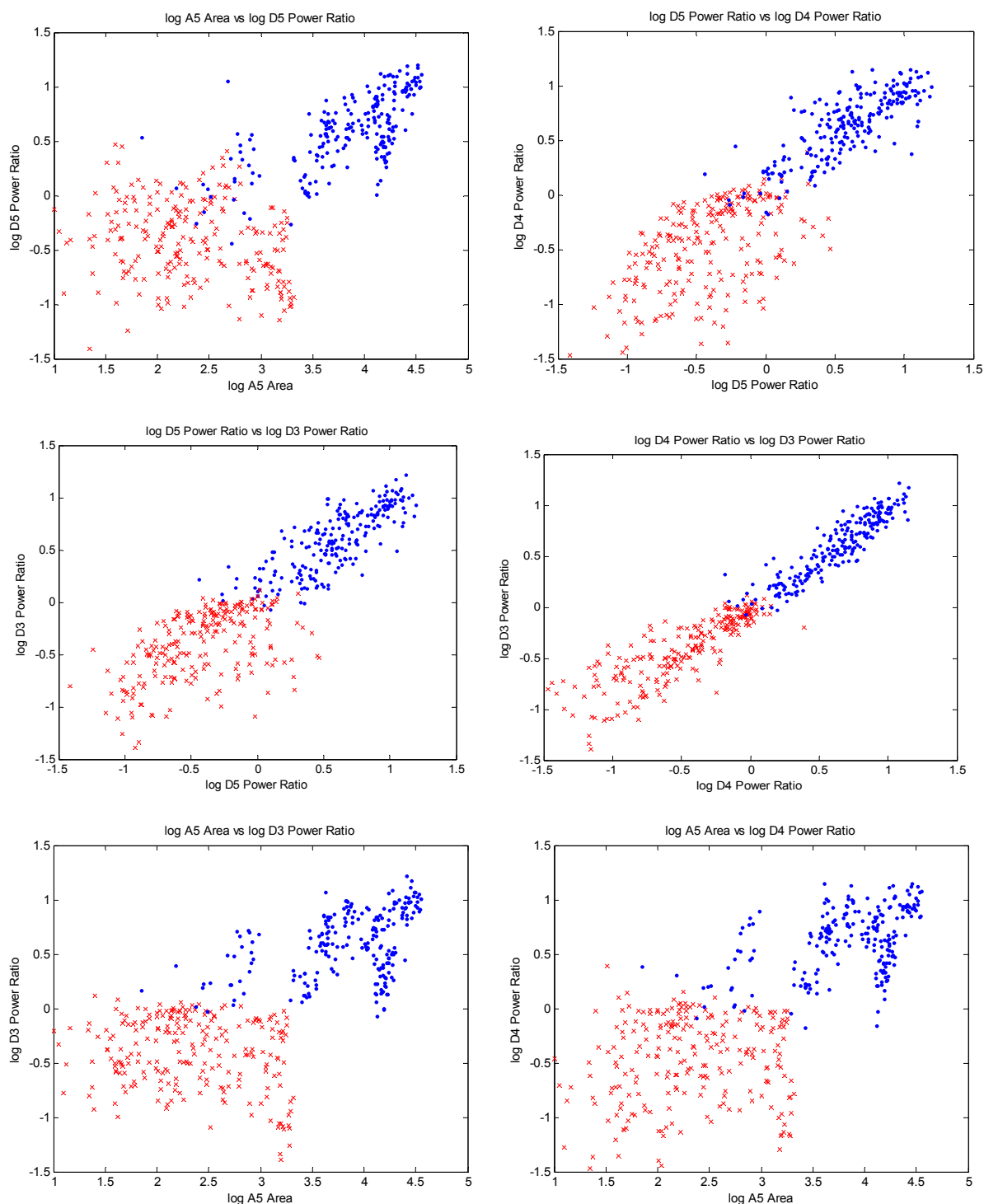

**Figure 6 – 2D Feature Spaces derived from the "known" DPG data set (a) A5area vs. xD3 (b)
A5area vs. xD4 (c) A5area vs. xD4 (d) xD5 vs. xD4 (e) xD5 vs. xD3 and (f) xD4 vs. xD3**

3.   NEURAL NETWORK CLASSIFIER

Neural networks are a powerful tool used to solve difficult classification (mapping) problems with complex decision regions that are often required to ensure separability between classes and a proven ability to realize non-linear discriminant functions.. The use of neural networks for classification is well documented and the requirements for training are well known. The standard multilayer feedforward neural network shown in Figure 7 was chosen due to its ability to learn mappings of any complexity, provided that the number of hidden layer neurons is sufficient to accommodate the number of separable regions that are required to solve a particular classification problem. In general, the network contains N_i inputs, N_h hidden layer neurons and N_O output layer neurons with no interconnections within a single layer. In the three-layer network shown, the connection weight between the ith input and j^{th} hidden layer neuron will be denoted as w_{ij} and v_{jk} will be used to denote the connection weight between the jth neuron in the hidden layer and k^{th} output layer neuron. A bias for the jth hidden layer neuron is denoted as b_j and the bias for the kth output neuron is $\hat{b}_k$. x^p denotes the set of P, N-tuple feature vectors $x_n \in \Re^N$, $x^p = \left[x_1^p, x_2^p, \ldots, x_N^p\right]$ used to discriminate between the different classes of artillery.
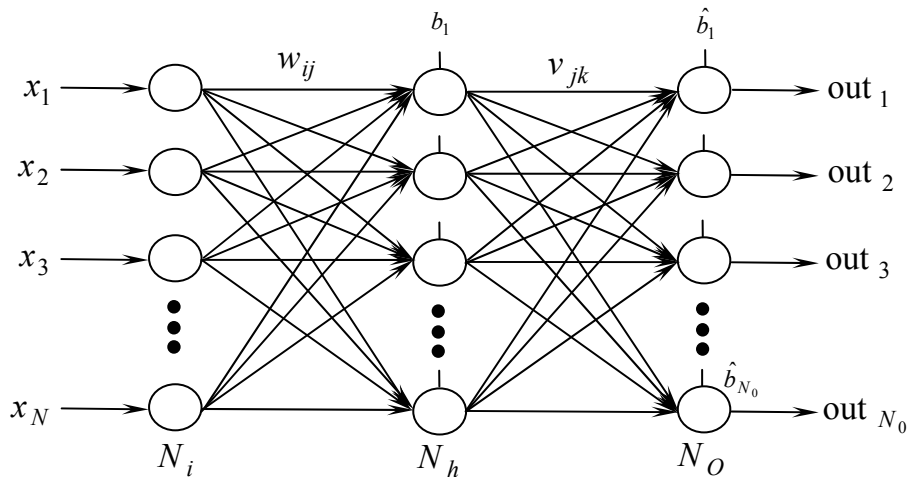

Figure 7– Standard Multilayer Feedforward Neural Network

4.1   RESULTS

Features were extracted from both data sets using the DWT as described in section 3, and the 4-tuple feature vector $x^p = \left[x_{D5}^P, x_{D4}^P, x_{D3}^P, A_{5AREA}^P\right]$ was constructed according to equations (5) and (6). Experiments were then conducted to measure the separability of the feature space and benchmark the performance of the proposed neural network classifier. The architecture shown in Figure 7, consisting of a single hidden layer neuron was trained using 22 randomly selected vectors from a total of 461 signatures made available from the data collection exercise at DPG. The training set comprised of 11 samples of HE data and 11 samples of Type A CB rounds collected at each of the 3 sensor sites. The neural network was trained with sample features representing a HE round would result as zero, while when features from a sample CB round applied would output a one based on the properties of our neural network. The network was trained with the total error of the system being less than 5e-3 and a learning rate of 0.1 was utilized. When tested against the remaining 439 signatures, the networked correctly classified 100% of the remaining 225 CB blasts and misclassified a total of 4 out 214 (or 98.1%) of the remaining HE rounds, for an overall performance of 99.1%. The rounds were classified based on the neural network generated weights as CB if the output value was greater than ½ and HE otherwise.

In a subsequent experiment, a neural network consisting of 4 hidden layer neurons was then trained using the entire dataset from the DPG test; a total of 236 Type A CB rounds and 225 HE signatures. The network was then tested against the data collected by NCPA at YPG. The network correctly classified 165 of the total of 166 CB rounds and misclassified a total of 6 out of 57 HE rounds, for a rate of 99.4% and 89.5% respectively. Neural networks consisting of up to 3 hidden layer neurons could not match or surpass the classification performance provided with the architecture comprised of 4 hidden layer neurons. A third experiment was undertaking utilizing the "so-called" blind data from DPG for which truth data was provided by the test facility. The data was tested using a neural network trained with 4 hidden layer neurons and against all the initial DPG data that was considered to be "not blind". The results obtained for these blasts provided correct classification results of 98.3% of all the CB and 95.7% of all the HE, providing further confidence in the neural network and the results of the classification. However, the same results were obtained when training a neural network comprised of 5 or more hidden layer neurons. Once again, the rounds were classified, as CB when the value produced was greater than ½ and HE otherwise. A summary of the neural network performance is shown in Table 1.

Table 1 - Summary of Classification performance results

Experiment #	Training Data	Test Data	Classification	Percentage
1	11 CB (DPG)	225 CB (DPG)	225 CB / 0 HE	100%
	11 HE (DPG)	214 HE (DPG)	210 HE / 4 CB	98.1 %
2	236 CB (DPG)	166 CB (YPG)	165 CB / 1 HE	99.4 %
	225 HE (DPG)	57 HE (YPG)	51 HE / 6 CB	89.5 %
3	236 CB (Blind)	230 CB (Blind)	226 CB / 4 HE	98.3 %
	225 HE (Blind)	184 HE (Blind)	174 HE / 8 CB	95.7 %

4.2 REAL TIME PERFORMANCE

The algorithm described in this paper was coded into a real-time environment using C++ and incorporated into an application for an acoustic based CBRN discrimination system into an unattended ground sensor (UGS) upon the PAWSS platform. The algorithm was embedded into PAWSS as part of a LOE to provide processed acoustic event data as added situational awareness to the user and the decision aide tool. A result is provided to the user via a graphical user interface (GUI) that indicates whether a burst event was a HE or potentially CB in nature. The sensor layout is shown in Figure 8. Microphones were emplaced at positions S1-S4 at sampling rates of 32KHz, 32kz, 16kHz and 6.25 kHz respectively. S3 was emplaced for the purpose of recording the muzzle blast, S2 was used to record impact events and S4 was used to test the real time implementation of the algorithm.
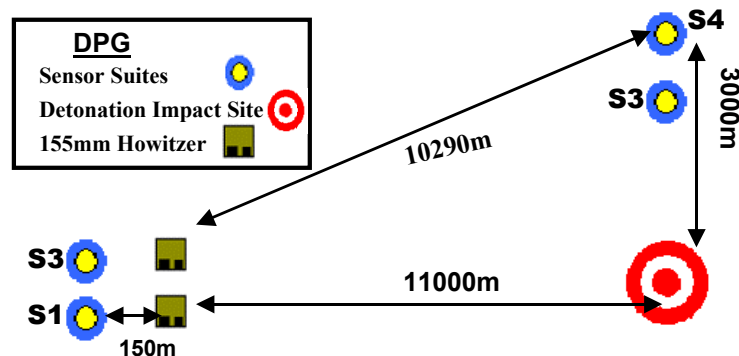

Figure 8 – Sensor Deployment at Dugway Proving Grounds

The results obtained for 38 airburst events resulted in 100% correct classification of the CB and HE single volley events at the ranges shown in Figure 8. The detonation ranges, airburst heights, ever-changing meteorological conditions, and artillery stock varying greatly during the 3-day test period provided a host of challenges for the algorithm classifying single volleys. The PAWSS LOE provided an opportunity to benchmark the algorithm against dual shot volleys for the first time. A total of 34 total airburst detonations were used to test against the dual shot volleys. The dual shot volleys were designed to simulate a large scale attack by simultaneously firing both howitzers followed immediately by a third singular round in a series of combinations. All possible arrangements for the 3 rounds of the two artillery types were employed (i.e. HE, HE, CB or HE, CB, HE or HE, CB, CB, or CB, CB, HE) to both mimic field conditions and mask airburst events. The algorithm classified 80% of all the HE rounds and 83.3% of all the CB events (cf. Table 2).

Table 2 - Summary of Classification performance results

Experiment # 4	Training Data	Test Data	Classification	Percentage
PAWSS LOE Single Shot	11 CB (DPG)	24 CB (DPG)	24 CB / 0 HE	100%
	11 HE (DPG)	14 HE (DPG)	14 HE / 0 CB	100%
PAWSS LOE Dual Shot	11 CB (DPG)	24 CB (DPG)	24 CB / 4 HE	83.3%
	11 HE (DPG)	10 HE (DPG)	8 HE / 2 CB	80%

5. CONCLUSION

In this paper, feature extraction methods based on the discrete wavelet transform and multiresolution analysis facilitate the development of a robust classification algorithm that affords reliable discrimination between conventional and simulated chemical/biological artillery rounds via acoustic signals produced during detonation. Amplitude dependant features provide the basis for previously developed discrimination algorithms, which vary dramatically due to signal attenuation and distortion resulting from various propagation effects. Measurements from multiple sensors can be used to obtain range information to a blast under these circumstances, which in turn maintains the potential for a high level of correct classification. In general, it was noted that when the distances from the detonation point to disparate sensor exceeds 1km; the probability of correct classification degrades dramatically, even though visual cues that can be used to exploit class specific attributes are still noticeable within the signature data.

The non-stationary, transient and often oscillatory nature of artillery blast signals may be characterized efficiently with wavelet bases that successfully capture the time-frequency distribution of such signal components. Wavelets are better suited for analyzing transient signals, as they are well localized in time and in frequency, and are able to take into account the scale of discrete signal components. To this end, the wavelet transform has been shown to provide a scalable time-frequency depiction of blast signatures and has revealed details that are not readily detectable using conventional signal processing techniques. Utilizing the idea of multiresolution analysis provided by the discrete wavelet transform, we were able to break the original signature into subband components thereby removing the higher frequency noise features and creating two sets of coefficients at varying levels of decomposition. These coefficients are obtained each time the signal is passed through a lowpass and highpass filter bank whose impulse response is derived from Daubechies db5 wavelet. Distinct features are obtained through the process of isolating the details of the higher oscillatory components of the signature (i.e. characteristic whining of the shrapnel for HE rounds and weak under pressure for CB rounds). The ratio of the energy contained within the details at varying levels of decomposition is sufficient in discriminating between the vast majorities of artillery blasts.

The discrete wavelet transform has been successfully employed to extract unique, disjoint feature sets that remain consistent for a given class of round and do not degrade dramatically with long-range propagation. Classification results using a neural network trained on such attributes show consistently reliable

discrimination of CB artillery rounds that surpasses 98%, even when the network is trained on data acquired during different field test experiments. In addition, the algorithms developed herein allow for the discrimination of base ejection type rounds, which were not part of the original training set used to train the neural network.

The algorithm developed herein were implemented at the PAWSS LOE there-by validating the distinct feature set extracted from the airburst events discriminating CB and HE detonated events. The feature set remains consistent for a given class of rounds (independent of payloads) and different field test experiments. Test results show that these features do not degrade dramatically as long-range propagation is increased. The real time implementation was tested at increased distances to the impact zone; upwards of 3000m with burst heights of upwards of 1000m. The system was put through several extreme conditions common to hostile environments and performed commendably against high wind gusts in excess of 30m.p.h., rain, rugged mountainous terrain and multiple shot volleys. The results of the PAWSS LOE test were 100% correct classification for single volley rounds, which the system was trained to solve. The algorithm trained only against single volleys for the first time was exposed and tested against multiple volley rounds. The system correctly identified 83% of the events providing impressive real-time results

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[2] Reiff, C., Farques, M., Gonski, D., "Discrimination of Chemical/Biological vs. High Explosive Artillery Rounds Using Acoustic and Seismic Data Fusion," SPIE, FL, November 2002.

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Reliable Classification of High Explosive and Chemical/Biological Artillery Using Acoustic Sensors.

US Army RDECOM-ARDEC

By: Dr. Myron Hohil, Mr. Sachi Desai, and Mr. Amir Morcos

OUTLINE

- Introduction

- Data Collection Exercise

- Signal Processing of Acoustic Signatures

- Real-Time Implementation of Algorithm

- Conclusion / Future Efforts

Purpose / Motivation

Chemical and Biological Weapon Threats and Needs

- Determining if explosive event contains High Explosive material or Chemical/Biological agent on the battlefield.

- Providing field commanders with greater response time using a stand alone acoustic sensor.

- Giving greater situational awareness to threatened soldiers.

Data Collection

Acoustic Signature Data Collection of Blast Events

- Data Collection 1.
    - Conducted by National Center of Physical Acoustics (NCPA) in cooperation with ARDEC.
    - 39, rounds fired.
    - 3 categories of rounds were used, HE, Type A CB, and Type B.

- Data Collection 2.
    - Conducted by DPG Team and U.S. Army Edgewood Chemical Biological Center (ECBC) .
    - 265, rounds fired.
    - 2 categories of rounds were used, HE and Type A CB.

Data Collection #1

A C O E Data Collection

Sensor Suites

Detonation Impact Site

Howitzer

Detonation Impact Site

5048m

1221m

860m

400m

970m

1390m

2119m

S 7

300m

Howitzer

4000m

500m

500m

600m

600m

800m

S 1

S 2

S 3

S 4

S 5

S 6
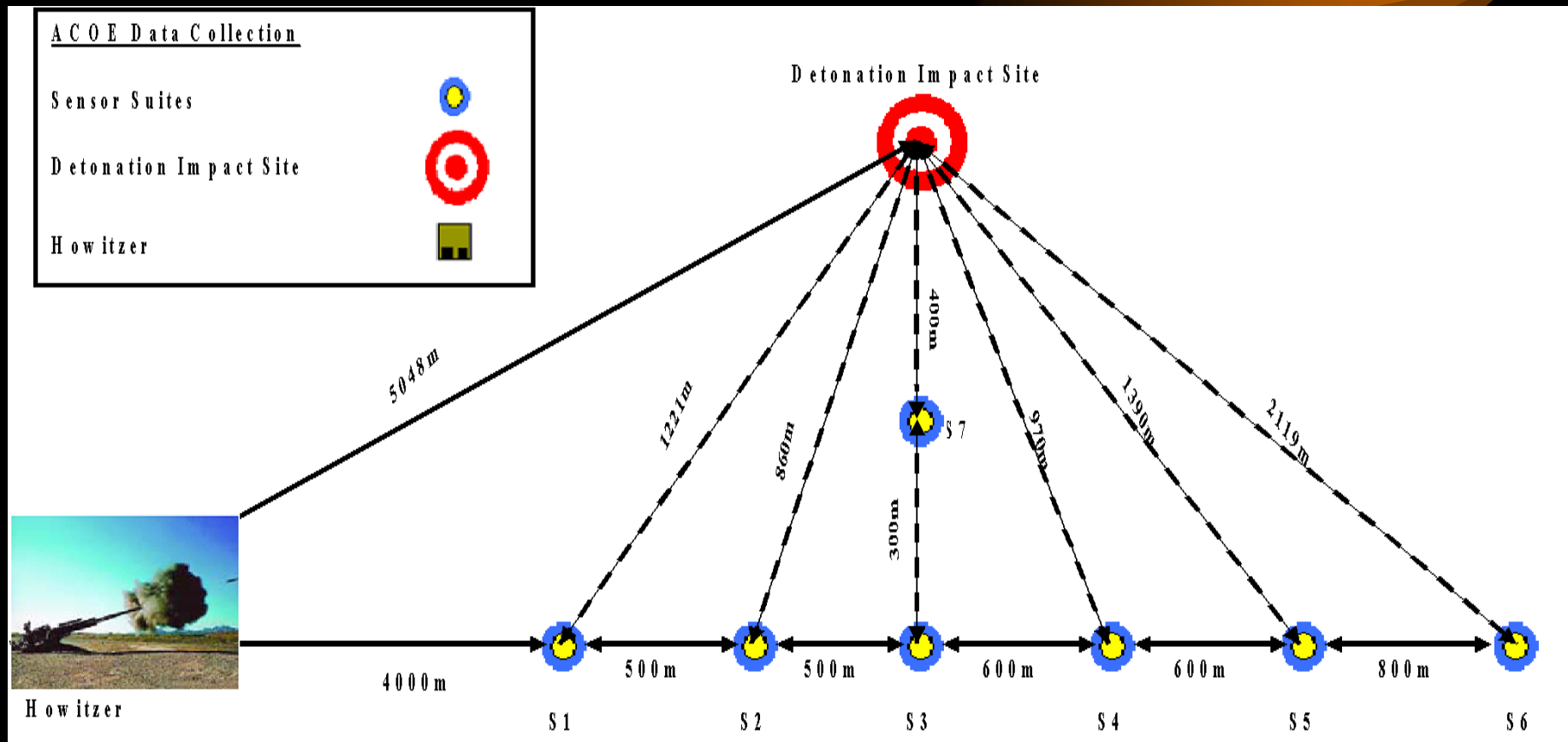
Typical Blast of HE Round

- High frequency precursors to the main blast.
  - Generated by Supersonic Shrapnel Elements.
- Large Amplitude of Main Blast.
- Large under pressure element .
  - Generated by large comparable weight of explosives rapidly burning.
- Short Duration Signatures.
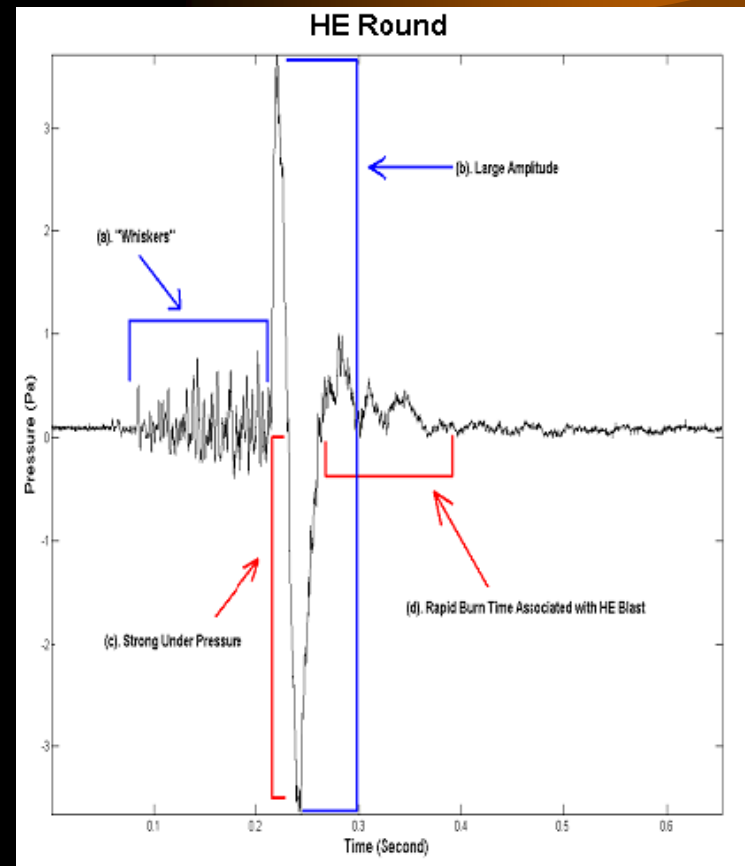
Typical Blast of Type A CB Round

- Small amplitude associated with main blast.
  - The explosive material is minimal compared to the comparable HE round type.
- Elongated burn time following main blast.
  - The deliberately slow to properly release the compounds.
- Weak under pressure.

Type A CB Round
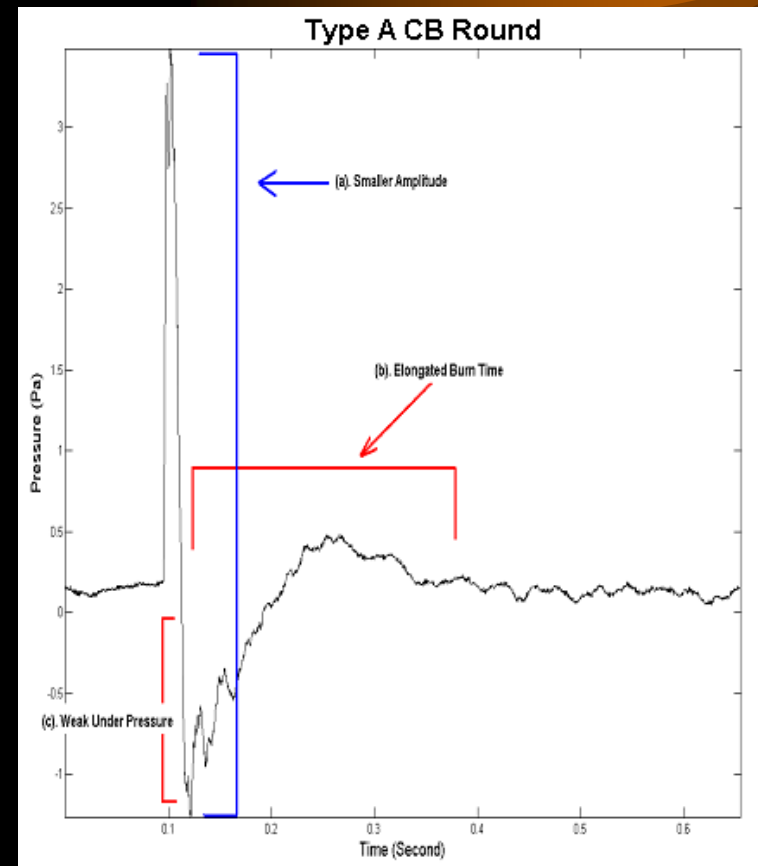
Typical Blast of Type B CB Round

- ## Short Duration Pulse.
  - Resulting from base ejection rounds.
- ## Weak Under Pressure.
  - Small amount of Explosives.
- ## Slow Burn Time.
  - Elongated to properly discharge contents of the round.

Type B CB Round

(a). Short Duration Pulse

(b). Slow Burn Time

(c). Weak Under Pressure

Pressure (Pa)

Time (Second)
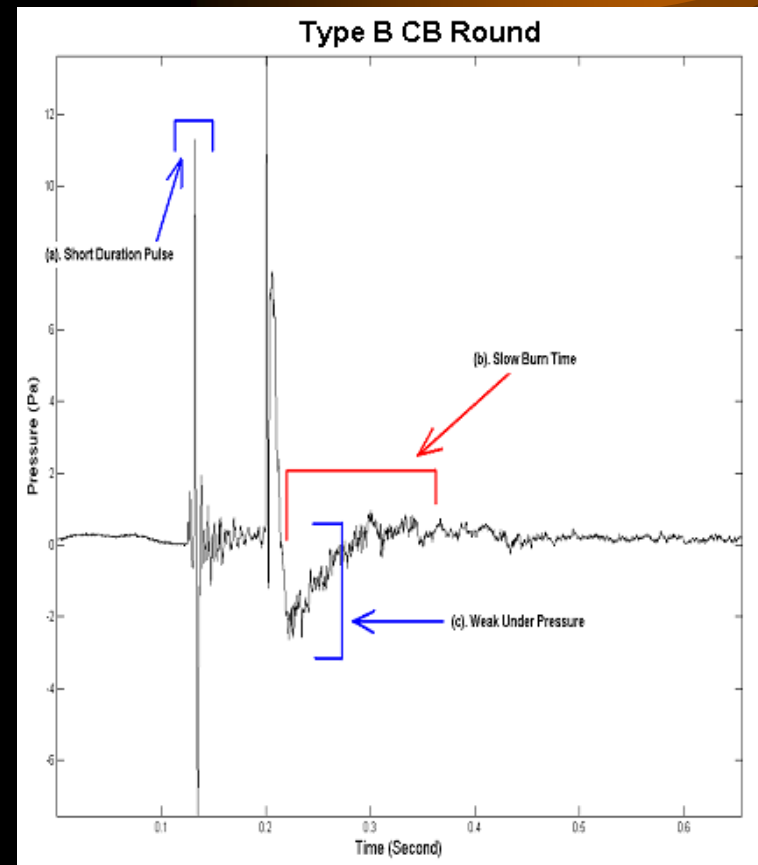
Signal Processing

Discrete Wavelet Transform (DWT)

- Derived from subband filters and multiresolution decomposition.
    - Coarser Approximation.
    - Removing high frequency detail at each level of decomposition.

- Acts like a multiresolution transform.
    - Maps low frequency approximation in coarse subspace high frequency elements in a separate subspace.

Defining Parameters

Scaling Function

$$\phi(x) = 2^{1/2} \sum_{k=0}^{L-1} h_{k+1} \phi(2x - k)$$

Wavelet Function

$$\psi(x) = 2^{1/2} \sum_{k=0}^{L-1} g_{k+1} \phi(2x - k)$$

Daubechies Wavelet, n = 5
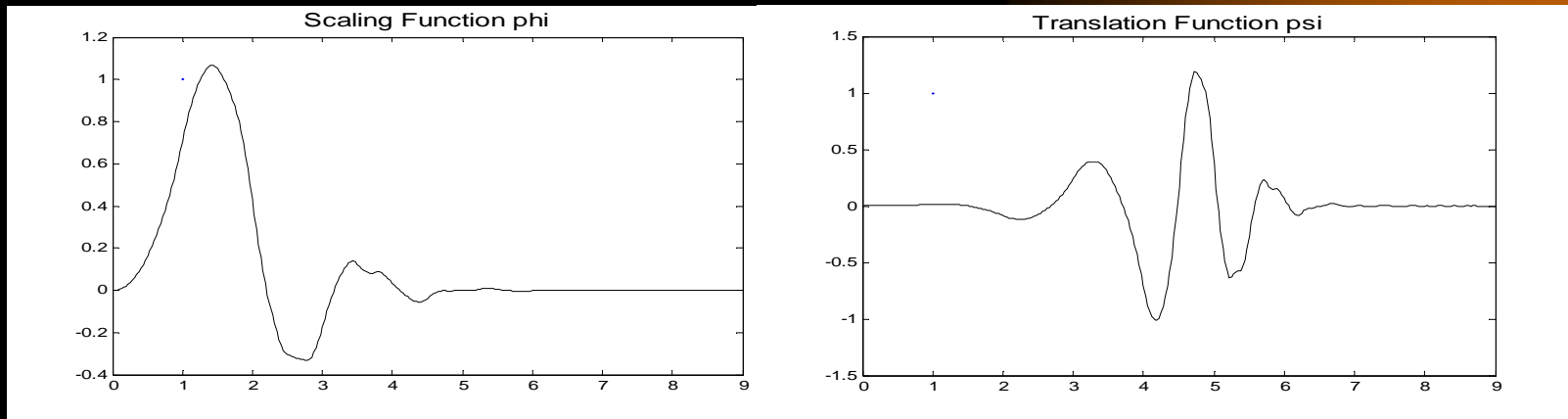
- Representation of the scaling and translation function of db5.
  - Scaling function resembles blast signature of the HE and CB rounds.
 - Provides the ability to approximate signal with the characteristic wavelet.

Multiresolutional Analysis

- Using a series of successive high pass and low pass filters to create a set of subspaces.
  - High pass filter obtains the details of the signatures while the low pass filter obtains a coarse approximation of the signal.
- The resulting banks of dyadic multirate filters separate the frequency components into different subbands.
  - Each pass through gives you resolution of factor 2.
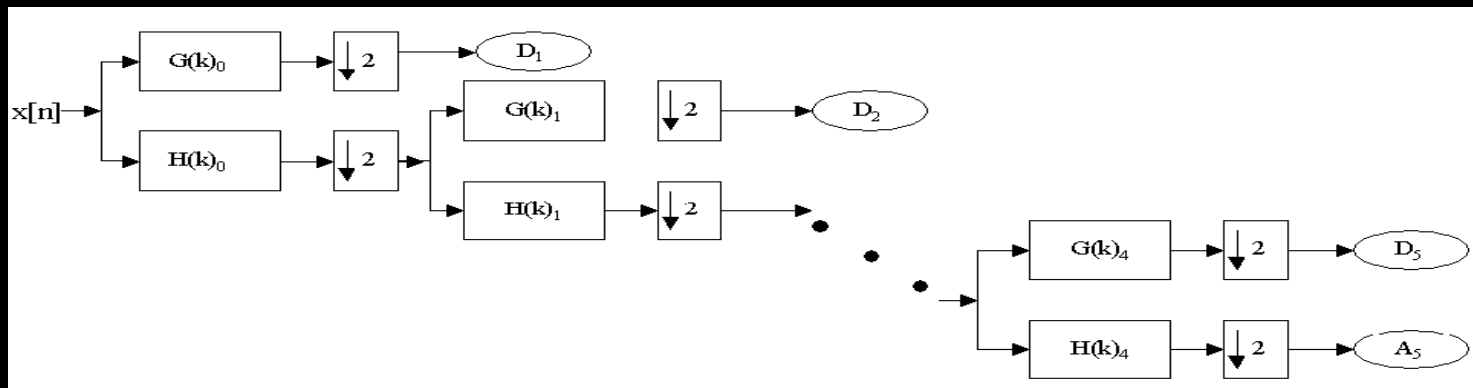
Effects of Wavelet Decomposition

- Wavelet decomposition to level 5 of three varying blast types from varying ranges.
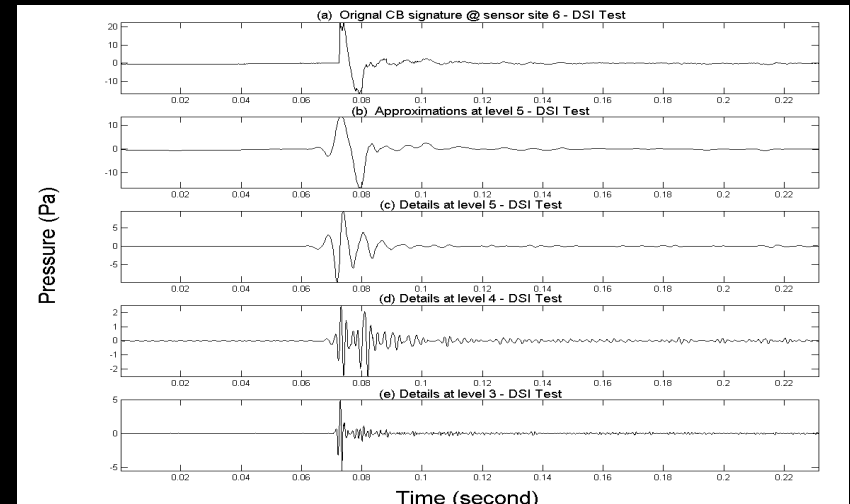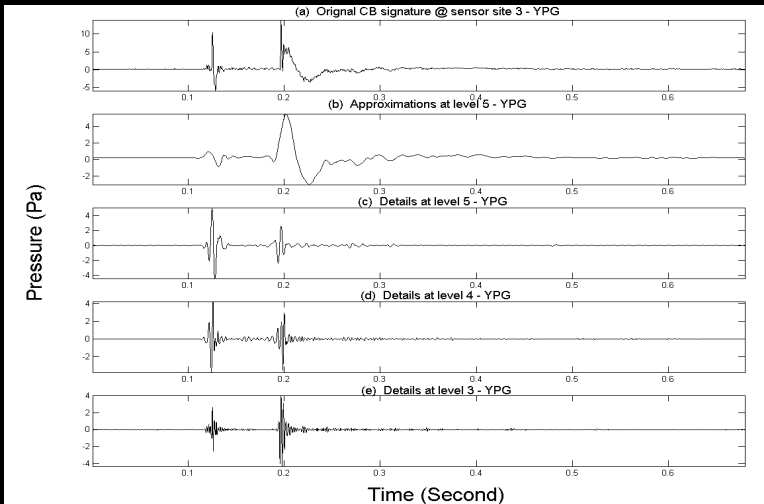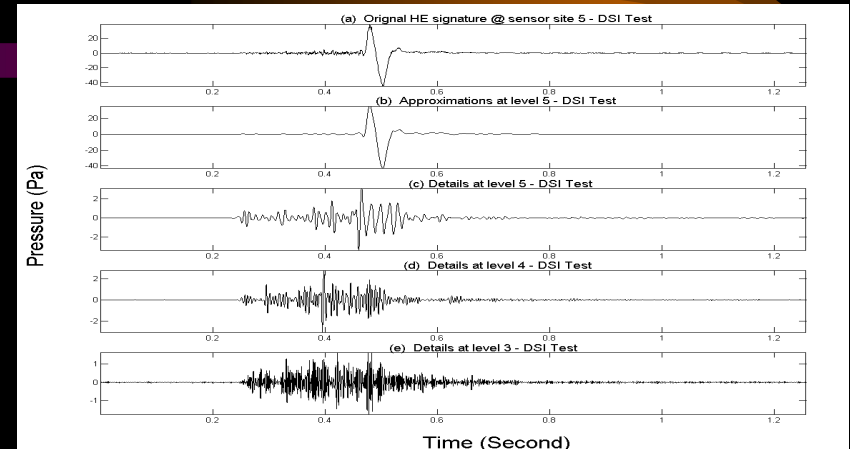
Wavelet Extracted Features

- Comprised of primitives derived from the normalized energy distributions within the details at level 5, 4, and 3 of the wavelet decomposition.

- Distribution of blast type differ greatly when taken prior to the max pressure, $D_k^- = \dfrac{1}{N} \sum_{n=t_0}^{t_P} \left| D_k(n) \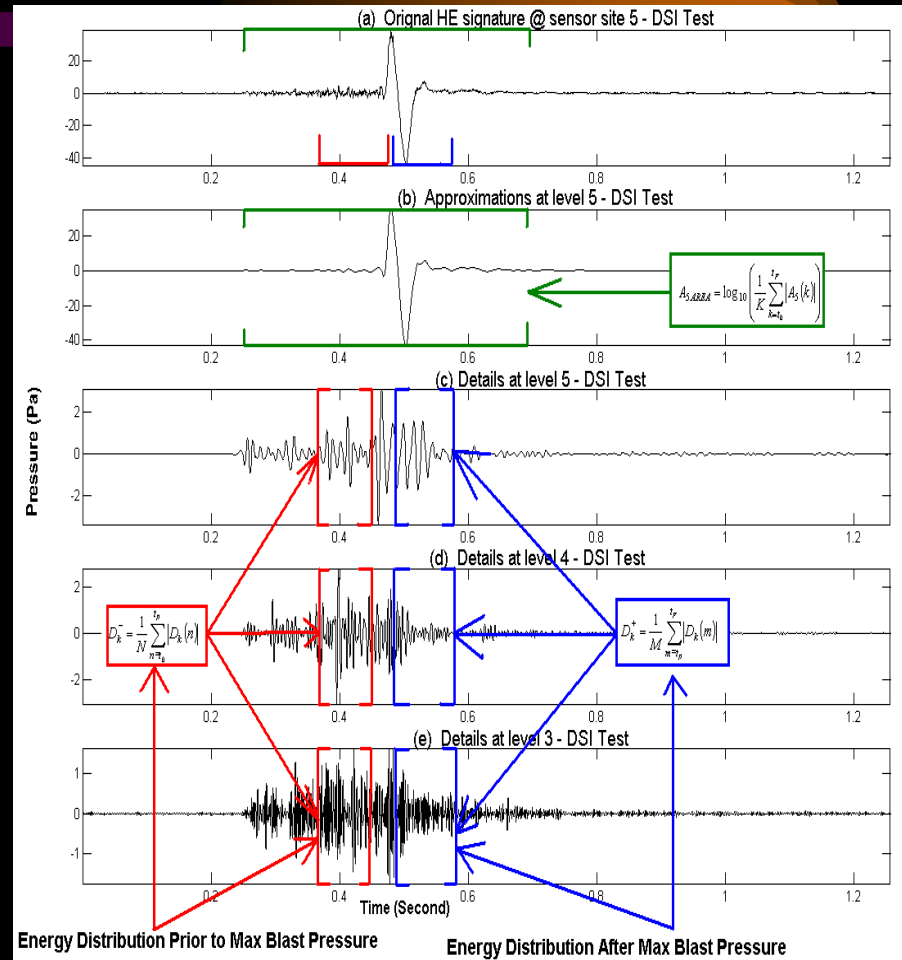righ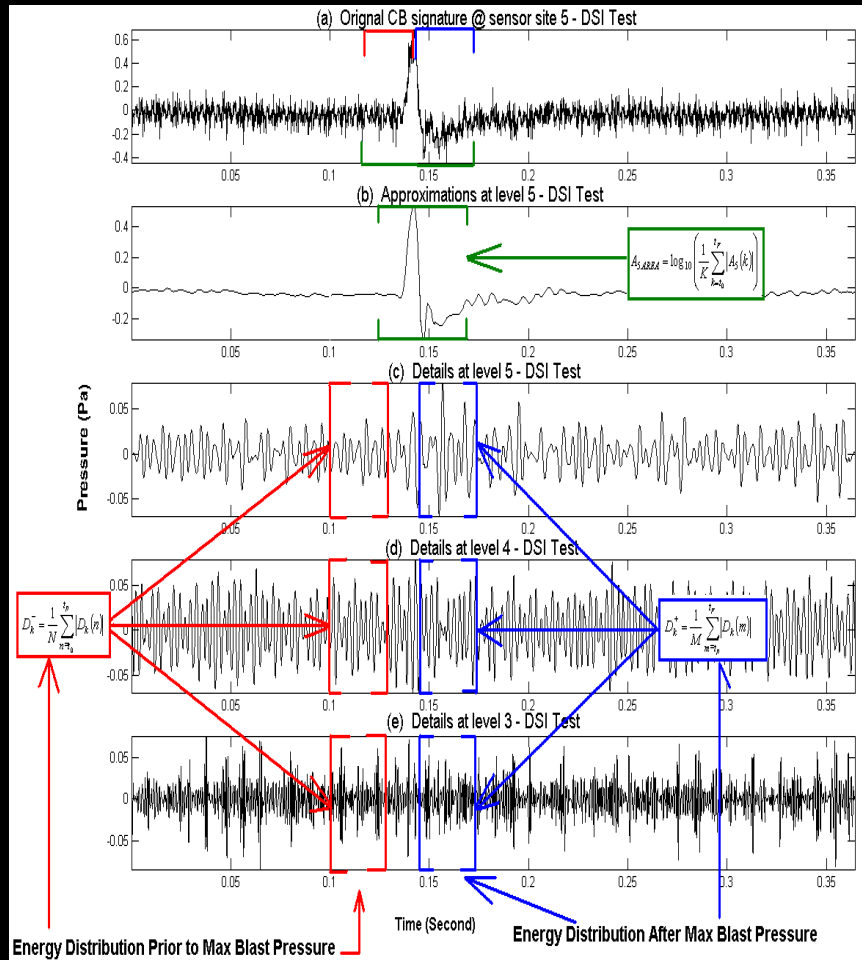t|$, with respect to distribution after the max blast, $D_k^+ = \dfrac{1}{M} \sum_{m=t_P}^{t_F} \left| D_k(m) \right|$.

- Resulting Ratio. $x_{Dk} = \log_{10}\left(\dfrac{D_k^-}{D_k^+} \right)$

- A5 area is a feature derived from wavelet coefficients at level 5.

- Integrating the magnitude of the area for the coefficients between the start and stop times.
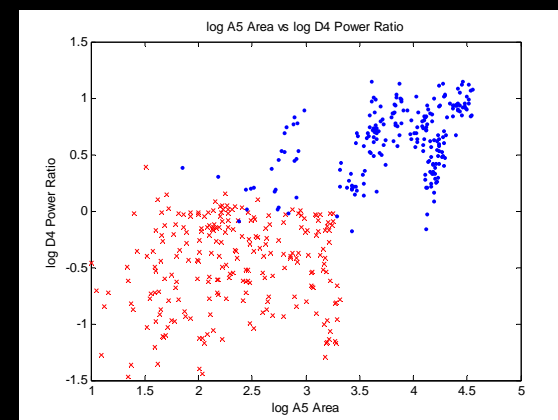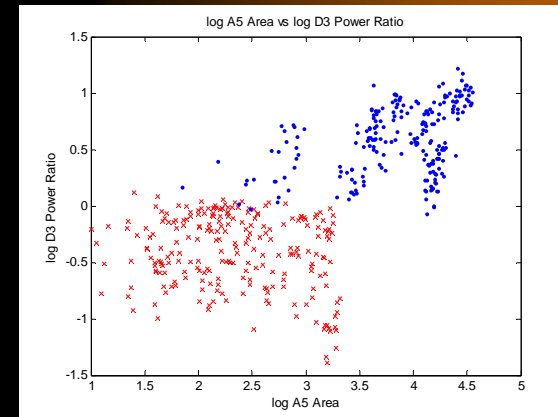
- $A_{5AREA} = \log_{10}\left(\dfrac{1}{K} \sum_{k=t_0}^{t_F} \left| A_5(k) \right| \right)$
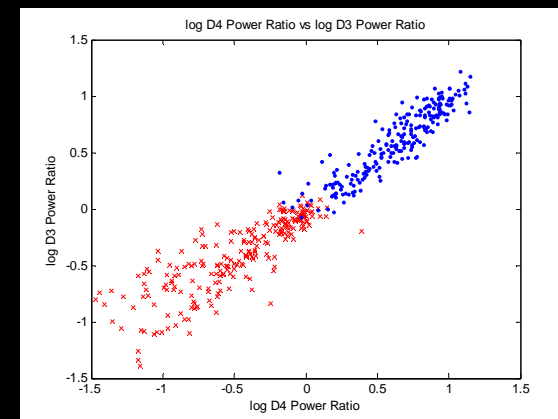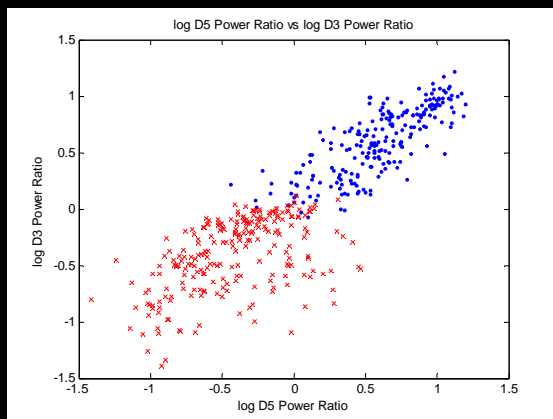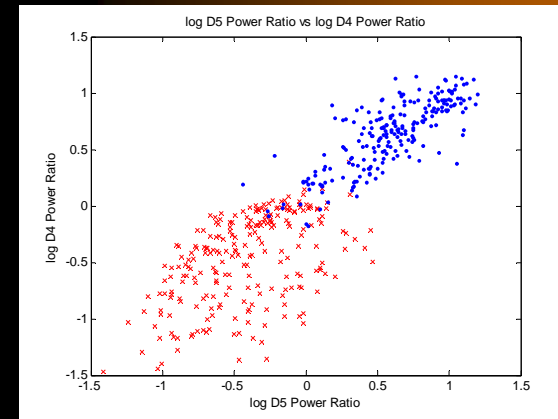
Extracted Features Using DWT

4-tuple Feature Space
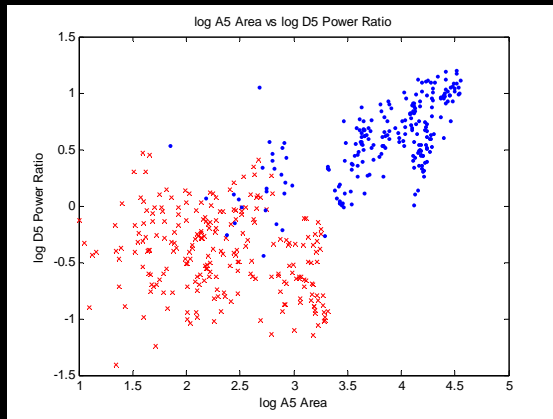
- This energy ratio leads to the discover of 4 features with A5 area that are not amplitude dependent.

- Our n-tuple feature space thus becomes a 4-tuple space, $x^p = \left[x_{D5}^P, x_{D4}^P, x_{D3}^P, A_{5AREA}^P \right]$, to be applied for classification.

log A5 Area vs log D3 Power Ratio

log A5 Area vs log D4 Power Ratio
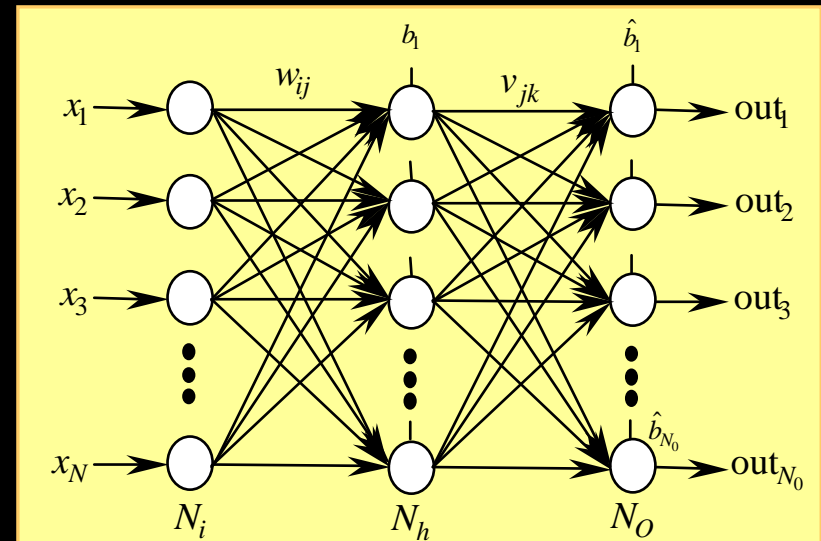
# 2-D Feature Space Realization

Airburst Discrimination

Neural Network

- Realize non-linear discriminant functions and complex decision regions to ensure separability between classes.

- Standard Multilayer Feedforward Neural Network.

- Number of hidden layer neurons depend on complexity of required mapping.

Results of Training Neural Network to DSI Data

- Feature Space created using DWT.
  - 4-tuple feature vector.
  - $x^P = \left[x_{D5}^P, x_{D4}^P, x_{D3}^P, A_{5AREA}^P \right]$
  - 22 randomly selected vectors from 461 signatures.

- Trained Neural Network to trained output data of 0.
  - Single hidden layer neuron.
  - Total error in equation after training is less then 5e-3.
  - Learning rate of 0.1.
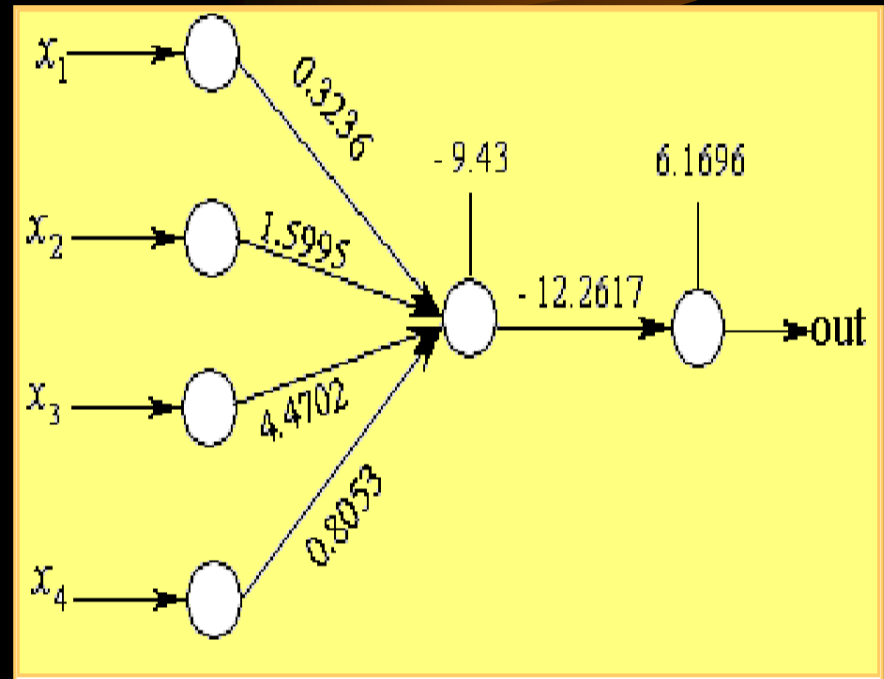
Results of HE/CB Discrimination

- Experiment 1.
  - Applying a neural network with the weights in the table 1 to DPG data, 99.1% Correct Classification.

- Experiment 2.
  - A neural network containing 4 hidden layer neurons trained using entire DPG dataset tested against NCPA dataset, 96.9% Correct Classification.

w_{i1}	w_{i2}	w_{i3}	w_{i4}	v_{j1}
11.6967	0.5343	-0.4958	-2.4991	-13.4966
4.6377	1.2455	3.5569	5.3068	13.3761
4.7023	0.9875	7.3951	8.902	-15.3761
-5.2246	1.481	2.6982	4.1203	-19.6513
-2.8169	1.4847	-18.9732	-23.6088	-14.286

Experiment #	Training Data	Test Data	Classification	Percentage
1	11 CB (DSI)	225 CB (DSI)	225 CB / 0 HE	100%
	11 HE (DSI)	214 HE (DSI)	210 HE / 4 CB	98.10%
2	236 CB (DSI)	166 CB (YPG)	165 CB / 1 HE	99.40%
	225 HE (DSI)	57 HE (YPG)	51 HE / 6 CB	89.50%

Blind Results of HE/CB discrimination

- Experiment 3.
  - Utilizing the neural network containing 4 hidden layers neurons trained against the entire "known" DPG data set was then tested against the "blind data" the results once compared with the truth resulted in 98.3% and 95.7% reliable classification.

w_{i1}	w_{i2}	w_{i3}	w_{i4}	v_{j1}
11.6967	0.5343	-0.4958	-2.4991	-13.4966
4.6377	1.2455	3.5569	5.3068	13.3761
4.7023	0.9875	7.3951	8.902	-15.3761
-5.2246	1.481	2.6982	4.1203	-19.6513
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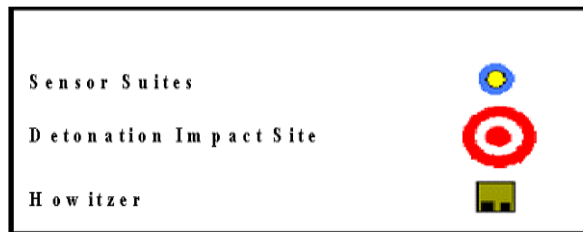| Experiment #	Training Data	Test Data	Classification	Percentage
3	236 CB (Blind)	230 CB (Blind)	226 CB / 4 HE	**98.3 %**
	225 HE (Blind)	184 HE (Blind)	176 HE / 8 CB	**95.7 %**

Real-Time Implementation

Experiment 4 Real Time Implementation

- Portable Area Warning Surveillance System (PAWSS).
  - 1yr Limited Objective Experiment (LOE).
  - Focused on the utility of cascading detection methodologies.
  - Combines Stand-off CBRN systems to address both force/installation protection.
- LOE Outcomes.
  - Operable Products leading to fully designed products that are sustainable.
  - Demonstration of capabilities within simulated battlefield environments of layered wide area cascading detection.
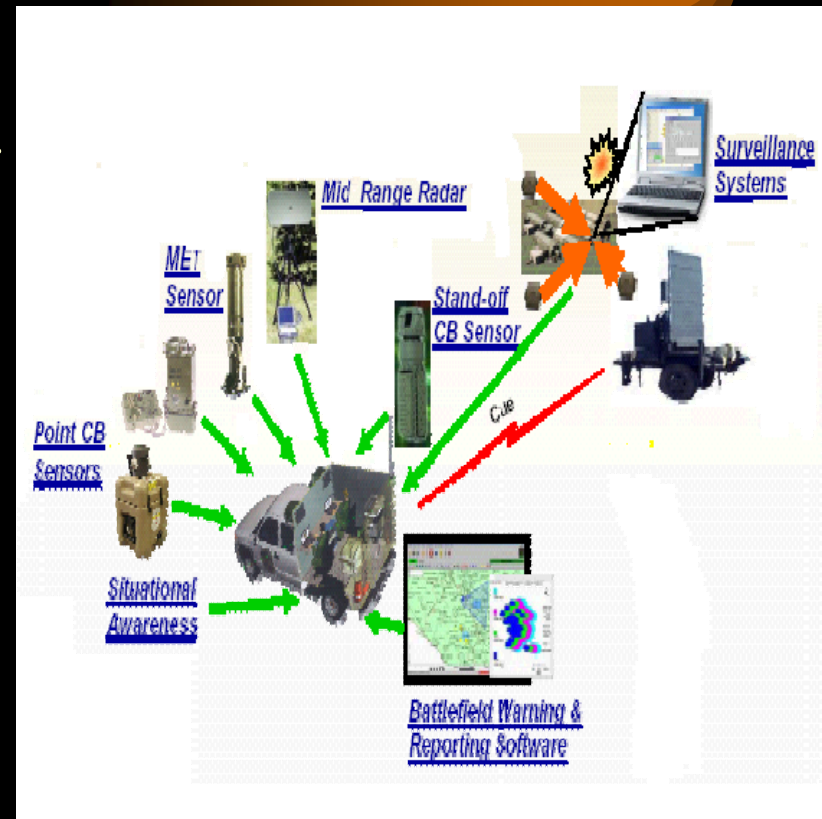
PAWSS LOE Test Layout

Artillery Variant	# of Rounds
HE	24
CB	48

Sensor Suites

Detonation Impact Site

Howitzer

S 4

10290m

2500 -3000m

11000m

150m
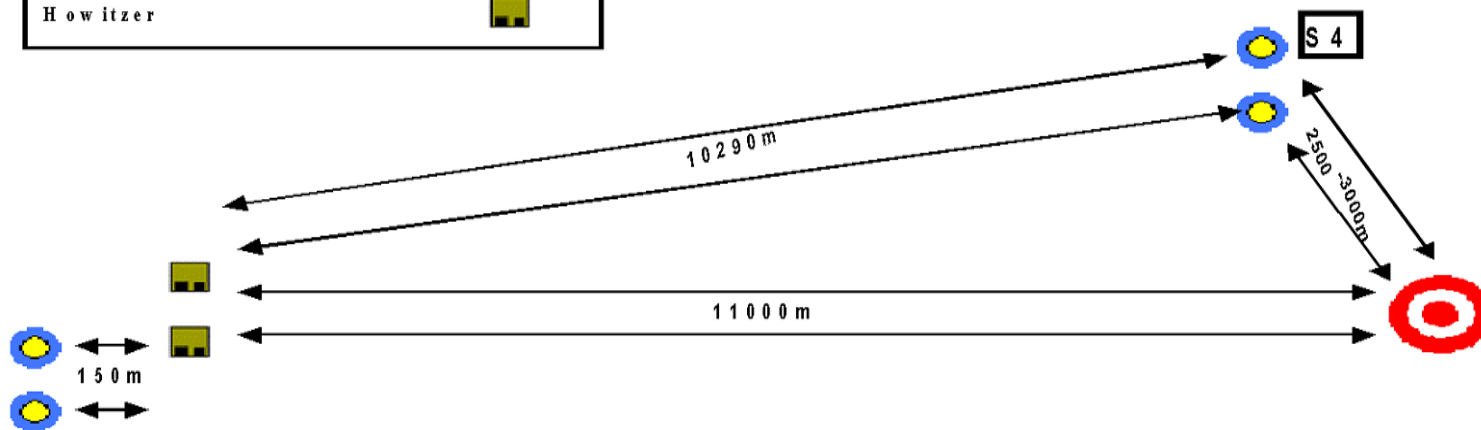
PAWSS LOE Results

- June 19th-28th Portable Area Warning Surveillance System (PAWSS) Limited Objective Experiment (LOE).

- Implemented real time version of CBRN Discrimination at PAWSS LOE conducted by ECBC.

- 100% single volley discrimination, never tested against dual volley, still 83%, also all event starts were detected for 100%.

- Assist in transition and support of acoustic element CBRNEWS ATD extending LOE efforts.

Event Type	# of Events	Discriminated Correctly
Single Round	38	38/38; 100%
Dual Round	34	28/34; 83%

Real Time Performance

- During June 21st and June 22nd, 2005 a proof of concept test was conducted for the acoustic CBRN discrimination algorithm.
  - PAWSS Test Site, DPG.
    - Acoustic System 2.5km-3km from Impact Zone.
  - A C++, real time algorithm was tested at DPG as part of the acoustic portion of PAWSS LOE conducted by JPM for NBC Contamination Avoidance at ECBC.
  - A total of 72 HE/CB rounds were detonated.
    - A howitzer fired 24 HE, and 48 CB rounds.
- Single Round Volley Results.
  - 38 Airburst Detonation (14 HE, 24 CB), 100% Correct Classification.
- Multiple Round Volley.
  - CBRN Algorithm Never Benchmarked in Lab vs. Multiple Rounds.
    - 2 Rounds simultaneously fired followed by a 3rd round fired soon as possible.
  - 34 Airburst Detonation (10 HE, 24 CB).
    - 17 events, each event consisted of 2 detonations.
  - 83% Overall Correct Discrimination of HE/CB.
    - 100% discrimination on all HE rounds.
    - 100% acoustic detection of all events.
    - 28 correctly discriminated from 34 detonations.
    - Shortcomings occur within the data acquisition process, limited by processing window size.

Conclusion

- Features extracted facilitate robust classification.
  - Reliable discrimination of CB rounds, 98.3% or greater of single volley events.
- The features this algorithm is based on go beyond previous amplitude dependent features.
  - Degradation due to signal attenuation and distortion is nullified and exceeds 3km in range propagation.
- Scalable time frequency representation uncovered non-readily detectable features.
  - Subband components remove higher frequency noise features.
  - Isolating the details of higher oscillatory components.
- Real time verification at PAWSS LOE of CBRN Discrimination Program Implemented in C++.
  - Single volley round discrimination in real time for all variants was 100%.
  - Dual volley round discrimination in real time for all variants was 83%, and detected an event 100% of the time.
- Wavelets can be possibly used to discriminate varying types of artillery projectile launches from impacts independent of range.
  - Utilizing wavelets and other signal processing techniques to perform a similar task as described within with refinement for the problem.
- Future Considerations.
  - Networking of sensors can provide TDOA abilities to further localize a threat.
  - Transitioning algorithm to CBNEWS ATD.

QUESTIONS…?

BACKUP

Acknowledgements

- Chris Reiff from Army Research Lab for his assistance in providing data sets from the DSI test.

- David Sickenberger and Amnon Birenzvige at Edgewood Chemical and Biological Center (ECBC) providing detailed documentation about the test at DSI.

- Edward Conley of JPM NBC CA at ECBC allowing us to participate in the PAWSS LOE.

Wavelets

- Efficiently represent non-stationary, transient, and oscillatory signals.

- Desirable localization properties in both time and frequency that has appropriate decay in both properties.

- Provide a scalable time-frequency representation of artillery blast signature.

Wavelet Analysis

Scale

Time